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Title: **Satellite remote sensing reveals impacts from dam-associated hydrological changes on chlorophyll-a in the world's largest desert lake**

Running Title: **Remote sensing the impacts of hydrological changes on chlorophyll**

Emma J. Tebbs[1*], Sean T. Avery[2], Michael A. Chadwick[1]

[1]King's College London, Department of Geography,

Bush House (NE) 4.01, 40 Aldwych, London WC2B 4BG, United Kingdom,

emma.tebbs@kcl.ac.uk, michael.chadwick@kcl.ac.uk

[2]Kenya Wetlands Biodiversity Research Team Member, National Museums of Kenya, and Associate, King's College London, sean@watres.com

*Corresponding author: Emma Tebbs, emma.tebbs@kcl.ac.uk

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Abstract – We present an approach that uses satellite products to derive models for predicting lake chlorophyll from environmental variables, and for investigating impacts of changing environmental flows. Lake Turkana, Kenya, is the world's largest desert lake, and environmental flows from the Omo River have been modified since 2015 by the Gibe III dam in Ethiopia. Using satellite remote sensing, we have evaluated the influence of these altered hydrological patterns on large-scale lake phytoplankton concentrations for the first time. Prior to dam completion, strong seasonal cycles and large spatial gradients in chlorophyll have been observed, related to natural fluctuations in the Omo River's seasonal discharge. During this period, mean lake chlorophyll showed a strong relationship with both river inflows and lake levels. Empirical models were derived which considered multiple hydroclimatic drivers, but the best model for predicting chlorophyll-a was a simple model based on Omo River discharge. Application of this model to data for 2015-2016 estimated that during the filling of Gibe III annual mean Lake Turkana chlorophyll declined by 30%. Future water management scenarios based on Gibe III operations predict reduced seasonal chlorophyll-a variability, while irrigation scenarios showed marked declines in chlorophyll-a depending on the level of abstraction. These changes demonstrate how infrastructure developments such as dams can significantly alter lake primary production. Our remote sensing approach is easy to adapt to other lakes to understand how their phytoplankton dynamics may be affected by water management scenarios.

Keywords: Lake Turkana, Gibe III dam, environmental flows, Omo River, water quality, flood pulse, cyanobacteria, MERIS

1. Introduction

The widespread dam construction across the globe has altered river flows, including through extensive dampening of seasonal and inter-annual variability in streamflows. These changes disrupt the ecology downstream (Poff & Zimmerman, 2010; Poff, Olden, Merritt, & Pepin, 2007) leading to ecosystem service and biodiversity losses (Avery, 2012). Recently there has been a surge of large-scale dam building in Africa, a trend likely to continue (International Hydropower Association, 2018). Thus, it is vitally important to quantify impacts of moderated inflows on affected aquatic ecosystems. Protecting these ecosystems to preserve environmental quality is inherently important especially as communities depend on associated ecosystem services for livelihoods and nutritional security (Ndebele-Murisa, Musil, & Raitt, 2010). For example, hydrological regimes are key drivers of phytoplankton dynamics which can regulate fisheries production in many African lakes (Melack, 1976).

This study investigated impacts of the Gibe III hydropower dam, situated on the Omo River, Ethiopia, on the ecology of Lake Turkana, the world's largest desert lake and the largest alkaline lake (Avery 2009, UNESCO, 2015). The lake is threatened by dams and downstream commercial plantations reliant on irrigation. The irrigation schemes reduce the water reaching the lake and the dams alter the magnitude and seasonality of the Omo River flood pulse (Avery, 2012, 2009). These changes disrupt the lake's water chemistry and ecology, including productive artisanal fisheries. Avery (2012) predicted that falling lake level from irrigation abstractions could reduce the lake's biomass volume by over half. Gownaris et al. (2016) predicted that the complete loss of seasonal oscillations in lake levels would lead to a decline in fish yields by at least two thirds. Yet the discharge magnitude and timing needed to sustain current environmental conditions have received little attention. Hence, investigation of impacts (e.g. water quality and lake productivity) from altered inflow patterns are desperately required (Avery, 2010, 2012, 2017). Turkana is nutrient-limited (Kallqvist et al., 1988) and nutrient input from the Omo is a critical factor driving lake productivity, as measured by chlorophyll concentrations (Avery, 2009, 2013; Hopson, 1982). However, the strength and form of the relationship between Omo inflows and lake chlorophyll concentrations are unknown.

Like many dams, Gibe III is within a transboundary basin (Figure 1). Effective management of transboundary river basins is critical for the UN Sustainable Developments Goals (Mccracken & Meyer, 2018), and there is a need to better integrate and value ecosystems within international transboundary water management frameworks (Mirumachi & Chan, 2014). Thus, an ability to predict the impacts of altered environmental flows on phytoplankton concentrations using independent global data from satellites will contribute to improved management of transboundary rivers.

Here we use remote-sensing products to investigate the spatio-temporal variability of Lake Turkana, prior to the filling of the Gibe III reservoir which began on 19th January 2015 (UNESCO, 2015), and to define an ecohydrological baseline. It should be noted that the effects of Gibe I and II dams were not studied as their storage is very small compared to Gibe III (UNEP, 2012). Due to the lake's vast size (~6,400 km^2), strong spatial gradients and remote location, satellite remote sensing was the only feasible monitoring mechanism. Furthermore, remote sensing allowed an examination backward in time of historic changes within the lake. Consequently, the study aimed to: (i) characterise natural spatial and temporal variability of water quality in Lake Turkana prior to the impoundment of the Gibe III reservoir; (ii) investigate relationships between lake chlorophyll-a (Chl-a) and hydro-climatic drivers (lake levels, Omo inflows, lake surface temperature and rainfall); and (iii) predict impacts of changed hydrological regime caused by Gibe III and irrigation abstractions on phytoplankton dynamics in Lake Turkana.

2. Materials and Methods

2.1 Overall approach

To address the study aims, several datasets were combined, including: satellite-based estimates of water quality, lake surface temperature and lake levels, modelled flow data for the Omo River, and ground-based rainfall measurements. These datasets were used to investigate the relationship between water quality and hydro-climatic drivers and to predict the influence of the Gibe III dam on lake ecology. The focus was to identify the main drivers of Chl-a, a proxy for phytoplankton biomass and primary productivity, this being the main factor governing the lake's productive fisheries. Finally, a predictive model was developed and applied to predict the impact of a modified hydrological regime on primary producer dynamics in Lake Turkana.

2.2 Study Area

Lake Turkana (3°35′N 36°7′E) lies in northern Kenya (Figure 1), within the African Rift Valley. The northern end of the lake crosses into Ethiopia. The lake lies in an arid region with erratic and low rainfall (150 to 350 mm annually) with highest rainfalls in April and November. Typically, the long rainy season takes place from March to May with a short rainy season in November. The Omo River, which provides over 80 % of the lake's inflow, enters at the northern end through the Omo delta wetlands (Hopson, 1982). The rainfall regime in the Omo basin varies, becoming increasingly unimodal to the north, with a single wet season extending from May to September (annual rainfall reaching 1,900 mm in the highland areas to the north (Avery, 2010)). The lake is the terminus in a closed basin; hence, the only output of water is through evaporation. Consequently, conditions are semi-saline (conductivity ~3,500 µS/cm) and relatively alkaline (pH ~9.4) (Avery, 2012). The lake has a mean depth of 30 m and a maximum depth of over 110 m, with shallower areas located in the north-western part of the lake (Figure 1; Hopson, 1982).

The physio-chemical properties of the basin result in high concentrations of cyanobacteria (Chl-a up to 2,760 mg m^{-3}, Kallqvist et al., 1988). Cyanobacterial biomass is key to sustaining the lake's productive fisheries, particularly for planktivorous species such as the Nile Tilapia (Kolding, 1993). Primary productivity in the main lake (1700 mg $Cm^{-2}day^{-1}$) is low compared to some African lakes (Lake Victoria, 2300 mg $Cm^{-2}day^{-1}$) but higher than others (Lake Tanganyika, 800 mg $Cm^{-2}day^{-1}$), and the productivity rates in sheltered areas and shallow lagoons are some of the highest ever recorded (36.7 O_2 mgl^{-1}) (Kallqvist et al., 1988). However, nutrient concentrations (PO_4 & NO_3 =~2 mg/L; Kallqvist et al., 1988) suggest oligotrophic conditions with productivity limited by nitrogen level.

The Omo-Turkana system has been progressively losing its pristine status with land-use change and a succession of dams, notably Gibe I, II and III in Ethiopia on the Omo, with Gibe IV and V still currently planned, and Turkwel in Kenya. The most recent of these, Gibe III, was inaugurated in December 2016. It is 243 metres high, with an electrical generating capacity of 1,870 MW (Avery, 2009). Other developments include the Kuraz sugar and other irrigation projects downstream (Avery, 2012; Figure 1). The dam and commercial plantation developments will impact water quantity and quality, including into Lake Turkana, leading to declines in lake levels and dampening of Omo seasonal inflow cycles (Avery, 2009; S. Avery, 2012, 2017).

2.3 Datasets

A range of water quality (Section 2.3.1) and environmental datasets (Section 2.3.2) were used in this study (summarised in Table 1).

2.3.1 Satellite-based water quality products

Water quality data were obtained from the European Space Agency's (ESA) Diversity II project (http://www.diversity2.info/). The products are based on Envisat's MERIS (MEdium Resolution Imaging Spectrometer) sensor with 300 m spatial resolution. These data are available from March 2002 – April 2012 as monthly aggregate maps. Analyses were restricted to months with an average of three or more observations per pixel across the lake surface to avoid spatial bias. Pixels around the edge of the lake were excluded to remove potential errors due to mixed pixels and/or adjacency effects.

The Optical Water Type (OWT) product uses the shape of the water-leaving reflectance to assign each pixel to one of seven optical classes (Moore, Dowell, Bradt, & Verdu, 2014). The

OWT was used to select the appropriate Chl-a algorithm; Lake Turkana was dominated by turbid waters (OWTs 6 and 7), indicating that the Maximum Peak Height (MPH) algorithm was most suitable (Brockmann Consult GmbH, 2015).

The MPH algorithm was developed for water bodies in South Africa, including some dominated by the cyanobacterium *Microcystis aeruginosa* (Matthews, Bernard, & Robertson, 2012). Therefore, it is well-suited to Chl-a retrieval in Lake Turkana, which is similarly dominated by *Microcystis aeruginosa* (Kallqvist et al., 1988). The MPH algorithm estimates Chl-a based on the height and position of the near infrared reflectance peak, which increases with increasing Chl-a concentration (Gitelson, 1992; Matthews et al., 2012). It has also been shown to be a robust method for retrieving Chl-a across a range of OWTs (Matthews & Odermatt, 2015).

TSM and turbidity products were obtained from the CoastColour algorithm (www.coastcolour.org), which uses two neural networks to perform atmospheric correction and retrieval of the inherent optical properties, with training ranges up to 100 $mg.m^{-3}$ Chl-a, 2000 $g.m^{-3}$ TSM and 5 m^{-1} Coloured Dissolved Organic Matter (CDOM).

2.3.2 Environmental Drivers

Environmental drivers were selected based on those which were likely to influence phytoplankton in Lake Turkana. Seasonal phytoplankton dynamics in African lakes have been linked to nutrient enrichment associated with rainfall, river discharge and wind-induced vertical mixing (Melack, 1979). Since Lake Turkana is nutrient-limited, inflows from the Omo River are expected to have a strong influence on phytoplankton dynamics (Kallqvist et al., 1988). Rainfall causes nutrient input through runoff from shoreline areas and this stimulates production (Hopson, 1982). The lake is well-mixed due to strong prevailing SE winds and as a result is well-oxygenated, with limited thermal stratification (Hopson, 1982).

Lake salinity is linked to lake levels (Avery, 2012), which in turn can influence phytoplankton communities (Hopson, 1982; Kallqvist et al., 1988), and lake level fluctuations are important as they influence nutrient cycling in the lake (Hopson, 1982). Elevated surface water temperatures can provide favourable conditions for cyanobacterial growth (Paerl & Huisman, 2008); however, in a well-mixed tropical lake like Turkana the influence of surface temperatures may not be significant.

Lake levels were obtained from the USDA/NASA G-REALM program (https://www.pecad.fas.usda.gov/cropexplorer/global_reservoir/). The product uses data from a combination of radar altimeter instruments to determine lake surface height. The product datum is the moving mean of the dataset with factors to adjust to mean sea level (USDA).

Monthly Omo inflows were estimated using a water balance model (Avery, 2009; Avery, 2012; Avery & Tebbs, 2018), which uses lake level changes from radar altimetry to estimate Omo inflows after accounting for evaporative losses and other river inflows.

Lake surface temperature estimates were obtained from the ESA ARCLake project (www.geos.ed.ac.uk/arclake/, MacCallum and Merchant, 2011). The product is based on remotely-sensed thermal emissions from the top ~500 µm of the waterbody. It has a 0.05° spatial resolution and a monthly time-step. The spatially reconstructed product was used, which fills in gaps due to cloud using a statistical interpolation method. Day and night lake surface temperatures were averaged to give a single temperature estimate.

Rainfall data were obtained from the Kenya Meteorological Department's Lodwar meteorological station (N 03° 07' 00" E 35° 37' 00"), the only rainfall station with long-term data continuity in proximity to Lake Turkana.

2.4 Data processing and statistical analysis

Data were processed using R statistical software. Seasonally-adjusted time series were produced for each variable by removing the seasonal component. Lake level change, ΔL, in metres per month was also calculated as:

$$\Delta L = L_{t+1} - L_t \qquad (1)$$

where L_t is the lake level in the current month and L_{t+1} is the lake level in the following month.

To identify collinearity between variables, the Pearson's correlation coefficient, *r*, for each pair of water quality (response) variables and each pair of environmental variables (drivers) was calculated. As expected, there was a strong correlation between Omo inflows and ΔL (r = 0.890). Surface temperature showed weak but significant correlations with ΔL, Omo inflows and rainfall (r = -0.350, -0.368 and 0.365 respectively). There were no other significant correlations amongst the environmental variables. Chl-a and TSM were highly correlated (r = 0.942). Turbidity exhibited a high degree of covariance with TSM and Chl-a (r = 0.668 and 0.722 respectively).

The optimum time-lag between lake Chl-a and all other variables was considered based on the lag (in months) which gave the best R^2 value; lags in the range -12:+12 months were considered. The optimum lag between TSM, Omo inflows and ΔL was zero. Turbidity peaked slightly after Chl-a with a time lag of one month. Chl-a correlated best with lake surface temperature with a lag or 5 months. Lake levels and rainfall showed low correlation with Chl-a ($R^2 < 0.5$) for all offsets. When seasonally-adjusted timeseries were used the R^2 values were low (< 0.5) at all offsets for most parameters, except for TSM and turbidity which both displayed zero time-lag from Chl-a.

Statistical models were developed to relate lake Chl-a to hydro-climatic drivers (Omo inflows, lake levels, ΔL, lake surface temperature, rainfall) and this was performed in two main stages: a simple model for predicting Chl-a from Omo inflows was derived - allowing predictions to be made about the impact of different inflow scenarios, and multiple linear regression was applied to investigate effects of all environmental variables on Chl-a in Lake Turkana. To determine which terms to include in the second model, multiple linear regression was applied to all environmental drivers (raw and seasonally adjusted datasets) using a random sample of 50% of the available data. This process was repeated 1000 times and the percentage of times each driver was significant in the model was recorded. The raw and seasonally adjusted Omo inflow and ΔL terms were significant in 59.5, 77.7, and 66.7% of the models respectively. Hence, these three terms were used in a final multiple regression model derived using the full dataset. All other variables were significant in less than 15% of models. Weighted least squares regression was used for the modelling to account for the non-uniform variance in the errors, using the reciprocal of Chl-a for the weights. The inclusion of lagged variables in the model did not improve model performance, so these results are not presented here.

2.3 Predicting the impacts of changing hydrology on chlorophyll dynamics

The MERIS-based water quality products used in this study were not available post-2012 and hence did not cover the critical period of the impoundment of the Gibe III dam. Therefore, the statistical models derived in this study were used to extend the Chl-a time series and to make future predictions. This was done in two stages:

1. Both the simple and multiple regression models were applied to lake level and Omo inflow data to extend the Chl-a time series up to April 2017 and to predict the impact of dampened and reduced inflows caused by the filling of the Gibe III reservoir on lake phytoplankton dynamics.
2. The simple model was applied to an expected scenario of Omo River discharge under operation of the Gibe III dam, and the long-term impact on Chl-a was predicted for different levels of irrigation abstraction.

2.4 Data Uncertainty and Validation

The reliability of the models developed depends on the uncertainty of the input datasets (Chl-a and hydroclimatic drivers). Unfortunately, there are no *in situ* Chl-a data for Lake Turkana for the period that MERIS was operational so the performance of the MPH Chl-a algorithm for the lake could not be assessed. However, the MPH product has been extensively validated across a range of OWTs (Brockmann Consult GmbH, 2015), and previous studies have demonstrated that MPH can predict Chl-a to within 50 mgm^{-3} for Chl-a <500mgm^{-3}, including in *Microcystis*-dominated lakes similar to Lake Turkana (Matthews et al., 2012).

Satellite altimetry data are a reliable proxy for *in situ* lake levels in ungauged waterbodies such as Lake Turkana (Avery, 2009; Avery & Tebbs, 2018; Velpuri, Senay, & Asante, 2012), and the G-REALM dataset has an accuracy of 3 – 5cm for large lakes (USDA, n.d.). ArcLake temperature estimates also have high accuracy (bias < 0.4 K; relative standard deviation, RSD = 0.5 K; (MacCallum & Merchant, 2011a).

The lake water balance model used to estimate Omo inflows is detailed in Avery (2012). There were no simultaneous *in situ* discharge data for validation; however, in Avery & Tebbs (2018), Omo inflows from the water balance model correlated closely with cumulative lake inflow simulations of the Omo-Gibe Master Plan (Woodroofe, 1996) and the Kuraz sugar plantation feasibility study (WWDSE, 2014).

3. Results

3.1 Spatial and temporal variability of water parameters in Lake Turkana

Mean Chl-a for Lake Turkana was 37.6 ± 28.4 mg m^{-3}, which corresponds to the eutrophic category of waters. TSM and turbidity were also high (30 ± 19.1 g m^{-3} and 25.7 ± 12.6 FNU respectively). The lake showed a strong latitudinal gradient in water quality (Figure 2) with the highest values being observed at the north basin where the Omo River enters (Chl-a: 400 mg.m^{-3}; TSM: 200 g.m^{-3}; turbidity: 50-60 FNU), and the lowest values in the south basin (Chl-a < 10 mg.m^{-3}; TSM ~ 0; turbidity: 5-10 FNU). Higher water quality parameter values were also recorded on the north-western side of the lake driven there by surface currents generated by the prevailing winds, and elsewhere due to inputs from seasonal streams and the Kerio and Turkwel rivers. At peak inflows, the Omo River plume extended southwards into the central section of the lake, hugging the western shore, and bringing higher concentrations of Chl-a and TSM into the central portion of the lake. Lake surface temperature also exhibited a strong spatial gradient, with north-western parts of the lake experiencing the highest temperatures because of shallower waters. Rainfall recorded at Lodwar Meteorological Station showed considerable seasonal and inter-annual variability, as is common in arid areas (Figure 3). The seasonal distribution of rainfall followed a bimodal pattern, with higher values usually occurring in April and November (Figure 3). Modelled Omo River inflows peaked in September, coinciding with peak Chl-a and TSM. The lake level time series for Turkana shows a complex pattern with seasonal variability overlaid onto long-term trends. Typically, water levels were highest in October, however under natural conditions there is significant inter-annual variability in lake levels. Day and night lake surface temperature showed a clear seasonal cycle, with the highest values seen in April and the lowest values in August following influxes of cool Omo water from the Ethiopian highlands (Figure 3). Water quality parameters in Lake Turkana exhibited strong seasonal cycles with noticeable inter-annual variation but no clear long-term trends (Figure 3). Both Chl-a and TSM concentrations peaked in September while turbidity peaked slightly later, in October (Figure 3).

3.2 Relationship between chlorophyll and hydro-climatic drivers

Lake-wide mean Chl-a showed a strong relationship with both Omo inflows and lake levels (R^2 = 0.69 and 0.76 respectively). . The simple model for predicting Chl-a from Omo inflows, I, was derived using weighted least squares, hereafter referred to as Model 1 (adjusted R^2 = 0.690; RMSE = 15.5 $mg.m^{-3}$; $p < 0.05$):

$$Chl\text{-}a = (9.91 \pm 1.4) + (0.038 \pm 0.003) \times I \quad (2)$$

A multiple linear regression model, hereafter Model 2, was developed based on raw and seasonally-adjusted Omo inflows, I and I_{adj}, and lake level change, ΔL, (adjusted R^2 = 0.852; RMSE = 10.8 $mg.m^{-3}$; $p < 0.05$):

$$Chl\text{-}a = (34.2 \pm 2.5) + (76.2 \pm 10.8) \times \Delta L + (0.026 \pm 0.004) \times I + (0.024 \pm 0.004) \times I_{adj} \quad (3)$$

Models 1 and 2 were used to predict lake Chl-a from hydrological parameters (inflows and lake levels) and the results were plotted against measured Chl-a estimates from the MPH algorithm (Figure 4).

3.3 Influence of modified Omo inflows on Chl-a dynamics in Lake Turkana

Models developed in Section 3.2 were applied to Omo inflow and lake level data for the period January 1993 – April 2017, in order to extend the Chl-a timeseries and predict the influence of changing hydrology on phytoplankton dynamics due to both the Gibe III dam and irrigation abstractions (Figure 4.C). Three key time periods were considered (i) pre-Gibe III: before the impoundment in January 2015; (ii) Gibe III filling: the period over which the reservoir was filling (2015 – 2016); and (iii) post-Gibe III: after the filling of the reservoir was complete, from 2017 onwards.

The seasonal pattern of river inflows and lake level change altered dramatically during the Gibe III filling period with peaks in April/May and November/December rather than a single peak in August/September which occurred pre-Gibe III (Figure 5); the magnitude of change was also greatly reduced. This altered seasonal pattern was also reflected in the Chl-a predictions (Figure 5).

There were differences in the Chl-a predictions of Models 1 and 2 during the Gibe III filling period (Figure 4 and Figure 5); Model 2 predicted a Chl-a peak in September because of the negative coefficient for I_{adj} in the model, which means that low seasonally adjusted inflows lead to higher Chl-a predictions. This does not make physical sense since essentially the model is predicting higher Chl-a because there are lower inflows than there typically would be in those months. Therefore, although Model 2 was better at reproducing Chl-a pre-Gibe-III, it is likely that Model 1 is more reliable for making predictions post-Gibe III, when seasonal inflow cycles are drastically different. Hence, future Chl-a projections were based on Model 1 only.

3.4 Future Chl-a projections for different flow management scenarios.

Potential Gibe III-regulated inflow scenarios were considered across various levels of irrigation abstraction. The hydrograph for Gibe III-regulated flows was calculated from the historic lake-modelled inflows. The following regulation rules were adopted to maintain a minimum of 455 m^3s^{-1} at all times and to smooth out inter-annual variations: (i) distribute flows according to the regulation pattern proposed by the dam design team (EEPCO, 2009); (ii) any flows < 455 m^3s^{-1} were then forced to equal 455 m^3s^{-1} and the Aug, Sept, Oct flows in the same year were reduced by the equivalent amount; (iii) the annual flow was smoothed to equal the long term mean by adjusting the Aug, Sept and Oct flows. More details of how inflow scenarios were generated can be found in Avery & Tebbs (2018). The future inflow scenarios and consequent Chl-a seasonality, predicted from Model 1, are shown in Figure 6.

Model 1 predicted a 30% reduction in Chl-a during the Gibe III filling period compared with pre-Gibe III levels (Table 2) For future Gibe III-regulated inflow scenarios, Model 1 predicted that mean annual Chl-a would remain unchanged under a no-abstraction scenario, but changes in the seasonal Chl-a pattern were predicted (Figure 6). For the abstraction scenarios considered, significant declines in Chl-a of 19-44%, compared with pre-Gibe III levels, were predicted depending on the level of abstraction (Table 2).

4. Discussion

4.1 Role of the Omo River in driving water quality variability in Lake Turkana

This research confirmed the critical role of the Omo River in influencing the spatial and temporal nature of Lake Turkana's water quality and subsequent productivity. Strong north-south gradients in Chl-a, TSM and turbidity were observed, with the highest concentrations occurring closest to the Omo River delta (Figure 2) where sediments, suspended and dissolved material, and nutrients transported into the lake drive phytoplankton growth and associated Chl-a concentrations. In addition to these river-induced signatures, lake morphology further contributes to these north-south patterns. This is mainly associated with deep areas in the southern sub-basin being beyond the direct influence of the Omo and Kerio / Turkwell river plumes. There were strong seasonal cycles in water parameters; a phytoplankton bloom and peak TSM occurred in September each year. This corroborates *in situ* observations (Hopson, 1982; Kallqvist et al., 1988), and also shows that the timing and magnitude of the bloom were relatively consistent from year to year. The bloom coincided with peak inflow rates from the Omo River, highlighting the key role that the flood pulse plays in regulating the ecology of the lake and maintaining the lake's productivity.

The high covariance between Chl-a and TSM confirms that increased sediment and suspended matter from the Omo River floods convey nutrients that trigger phytoplankton blooms. The associated sediment load would also reduce light penetration, meaning less light available for photosynthesis; however, since the lake tends towards nutrient limitation, inputs from the river have a net positive effect on productivity. Chl-a typically makes up roughly 1–2% of phytoplankton biomass (Eaton & Franson, 2005); applying this figure to the MPH Chl-a estimates showed that the proportion of TSM due to phytoplankton biomass in Lake Turkana was 6 – 11%.

Hydrological drivers dominated Chl-a dynamics in Lake Turkana. There was a strong correlation of Chl-a with both Omo inflows and lake level change. These hydrological variables capture two key nutrient inputs: from the catchment (Omo inflows) and from the shoreline (surface runoff and lake level change, which mobilize nutrients from the terrestrial-aquatic transition zone; Hopson, 1982; Wantzen, Junk, & Rothhaupt, 2009) Wantzen et al., 2009). The hydrodynamic regime is important in controlling the input and re-suspension of nutrients in tropical lakes and consequently has a strong impact on productivity (Kolding & van Zwieten, 2012).

In Lake Turkana, Chl-a fluctuations were best represented by a simple linear model based on Omo inflows alone (Model 1). However, in many lakes, other variables will be important, and relationships may be complex and non-linear. In higher latitude lakes seasonal changes in radiant energy and thus water temperature will be an important factor, whereas in some tropical African lakes, phytoplankton seasonality is dominated by wind, water column structure and circulation (Talling, 1986), e.g. Lake Kivu (Sarmento, Isumbisho, & Descy, 2006), Lake Tanganyika (Horion et al., 2010) and Lake Victoria (Cózar et al., 2012).

4.2 Impact of modified flows due to the Gibe III hydropower dam on phytoplankton dynamics

The Gibe III dam and downstream abstractions for irrigation plantations dampened seasonal oscillations and reduced inflows (Avery, 2017). Our results suggest a 30% decline in lake Chl-a during the Gibe III filling period and a change in phenology due to the absence of the floods in August/ September. Results based on future Gibe III-regulated scenarios show that regulation leads to dampening of Chl-a seasonality, with a reduced range (difference between the highest and lowest months) of 30 $mg.m^{-3}$ compared with 51 $mg.m^{-3}$ pre-Gibe III. Future abstractions for irrigated agriculture were predicted to cause substantial declines in mean annual Chl-a, ranging from 19 – 44% depending on the level of abstraction. This decline in primary producers will be further compounded by the trapping of sediments and other water borne matter behind the dams (Avery, 2012). However, it is possible that water clarity will increase, leading to less light limitation and deeper photic zones. Once Gibe IV (Koysha) is in place, 80% of the inflow to the lake will be regulated, leading to further dampening of flood inflows and reductions in Chl-a in the lake (Avery & Tebbs, 2018); the impoundment of Gibe IV is planned to commence in 2020 (ibid.).

4.3 Reliability of model predictions

This study has shown how satellite datasets can be used to derive models that can predict the impact of changing environmental flows on Chl-a, including for remote and 'data poor' waterbodies. The remote nature of Lake Turkana unfortunately meant that not all model inputs could be validated for the lake due to a lack of simultaneous *in situ* observations, but the satellite products used have been validated extensively for other systems (Section 2.5). Chl-a estimates from the MPH algorithm (Figure 2) were comparable with the limited in situ Chl-a observations that are available for the lake (1.7 – 599 $mg.m^{-3}$, Tebbs & Avery unpublished data for 2016; Ferguson's Gulf: 94 - 2760 $mg.m^{-3}$, Kallqvist et al., 1988; 100-800 $mg.m^{-3}$, Hopson, 1982; central part of Lake Turkana: 2-4 $mg.m^{-3}$, and 13 $mg.m^{-3}$ during phytoplankton bloom, Kallqvist et al., 1988). In addition, previous studies have shown that MPH can predict Chl-a to within 50 mgm^{-3} for Chl-a <500mgm^{-3} in other turbid *Microcystis*-dominated waterbodies (Matthews et al., 2012). Above 500 $mg.m^{-3}$, higher uncertainties are likely, but this only applied to a small proportion of the lake surface. The south basin of Lake Turkana was dominated by clear waters (OWTs 1 and 3), so future studies should investigate alternative Chl-a algorithms for this part of the lake.

Although the multiple regression model (Model 2) could reproduce pre-Gibe III's Chl-a seasonality more accurately than Model 1, it was unreliable for post dam predictions. This highlights the need for future work to further validate the models and confirm the changes in the lake taking place during the crucial filling period and beyond. In future work, the authors will use data from other satellite sensors (e.g. Sentinels-2 and 3) to extend the Chl-a series for Lake Turkana to: investigate the long-term consequences of the dam on primary producers, test the predictions made in this study, and validate and improve the models presented here. Nevertheless, our approach using remotely-sensed data and simple statistical models has provided valuable insights into the future condition of the lake due to changes in water management.

5. Conclusion

There has been a resurgence in large dam building globally, and particularly in Africa, but the potential impacts of these developments on downstream aquatic ecosystems are often poorly understood and inadequately monitored. Here we have demonstrated an approach using satellite data to derive models relating lake Chl-a seasonality to environmental drivers (inflows, lake levels, temperature, rainfall), which can then be applied to predict the impact of altered hydrological regime on lake productivity. Since our approach is based on easy-to-access satellite products it can readily be applied to other lakes globally. This is the first time such an approach has been used to study the Chl-a concentration changes brought about by dam development. Measures of primary productivity can improve assessments of fish yields (Melack, 1972). Thus, our method can assist managers and fisheries scientists in predicting the impacts of altered hydrological regime on fish biomass and catch.

This study has highlighted the significant impact that moderated environmental flows, due to dams and other developments, can have on the ecology of large lakes; in this case the largest desert lake in the world (Lake Turkana) in northern Kenya. Our results have confirmed the critical role of seasonal Omo River inflows in driving water quality and primary producer dynamics in Lake Turkana. Chl-a was strongly related to both Omo inflows and lake level change, and a simple linear regression model based on Omo inflows alone was able to predict Chl-a with an R^2 = 0.690 and RMSE = 15.5 mg.m^{-3}. Gibe III dam's operations have already modified hydrological cycles through its filling and flow regulation that dampened the seasonal flood volume of the Omo River. Consequently, this study predicted large declines in lake Chl-a during the Gibe III filling period (30%), as well as changes in phytoplankton bloom phenology. Projecting into the future, Gibe III's flow regulation will dampen Chl-a seasonality, reducing the range between the highest and lowest months from 51 to 30 mg.m^{-3}, and irrigation abstractions will lead to a decline in mean annual Chl-a of 19 – 44% depending on the level of abstraction. The dam has inbuilt release capacity to simulate floods, but there is no commitment to release these floods long term. The future Gibe IV and V projects, planned downstream of Gibe III, will further dampen the flood inflows of Lake Turkana, and our research has confirmed the importance of maintaining such ecological flows to the lake, including an adequate annual flood pulse that supplies vital nutrients to sustain the lake's ecology and thus its productive indigenous fisheries upon which local people rely.

Data Availability Statement

The modelled chlorophyll data for Lake Turkana that support the findings of this study are available from the corresponding author, EJT, upon reasonable request.

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Tables:

Table 1. Summary of the water quality and environmental datasets.

Source/Sensor	**Parameter**
Diversity II /MERIS (Brockmann Consult GmbH 2015)	Chlorophyll-a Total Suspended Matter Turbidity Optical Water Type
ArcLake /AATSR (MacCallum and Merchant 2011)	Lake Surface Temperature
Kenya Meteorological Department	Rainfall
USDA/NASA G-REALM	Lake levels
Water Balance Model (updated from Avery 2012)	Omo River inflows

Table 2. Predicted annual mean Chl-a for Lake Turkana and percentage change from pre-Gibe III value shown in brackets as predicted by Model 1.

Hydrological Regime		**Chl-a Model 1 ($mg.m^{-3}$)**
Pre-Gibe III (Before 2015)		35
Gibe III filling (2015 –2016)		24.7 (-29.7)
Future Gibe III-regulated scenarios (2017 onwards)	No abstraction	35 (0)
	26% abstracted	28 (-19)
	39% abstracted	25 (-28)
	52% abstracted	23 (-37)
	65% abstracted	19 (-44)

Figures:

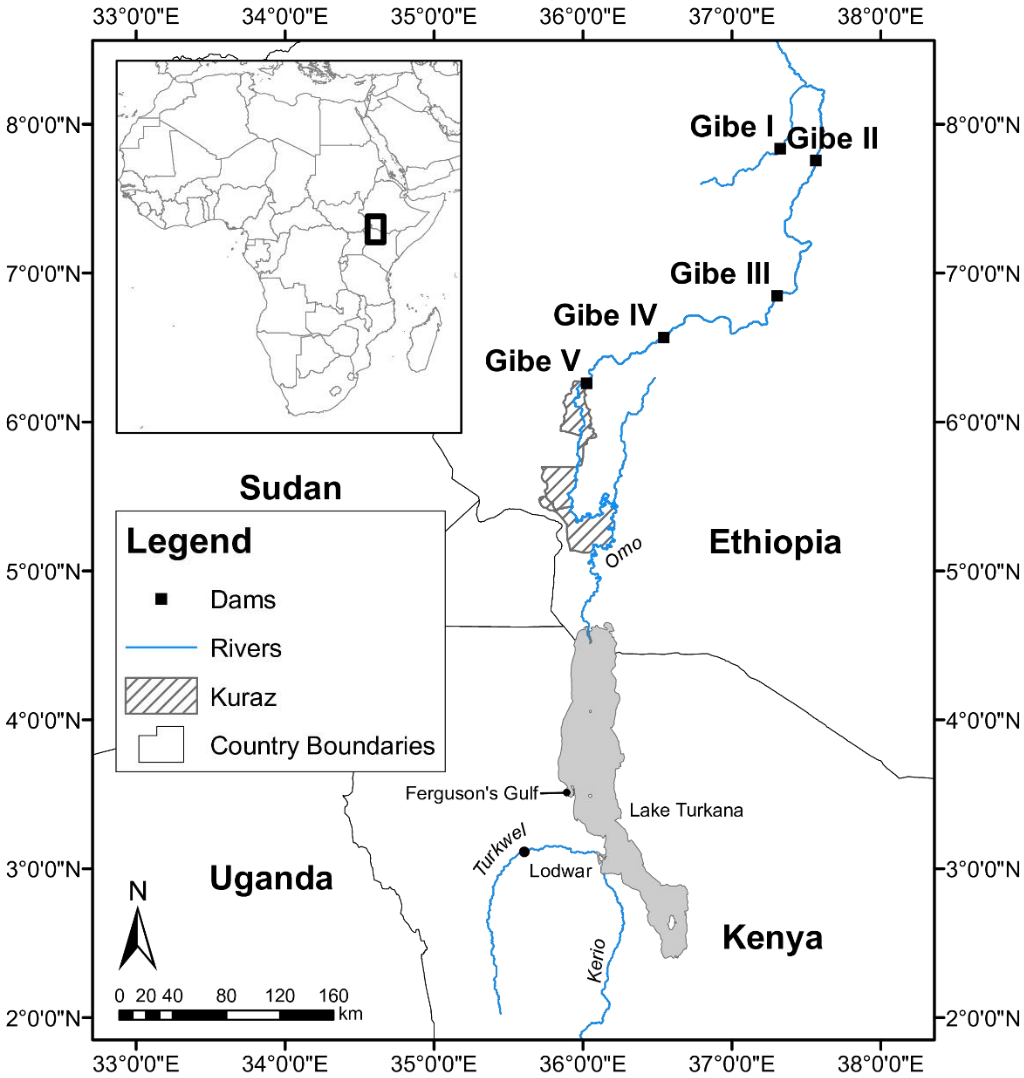

Figure 1. Map of Lake Turkana and surrounding region. Bathymetric map for Lake Turkana (contours at 10 m intervals) digitised from Hopson (1982).

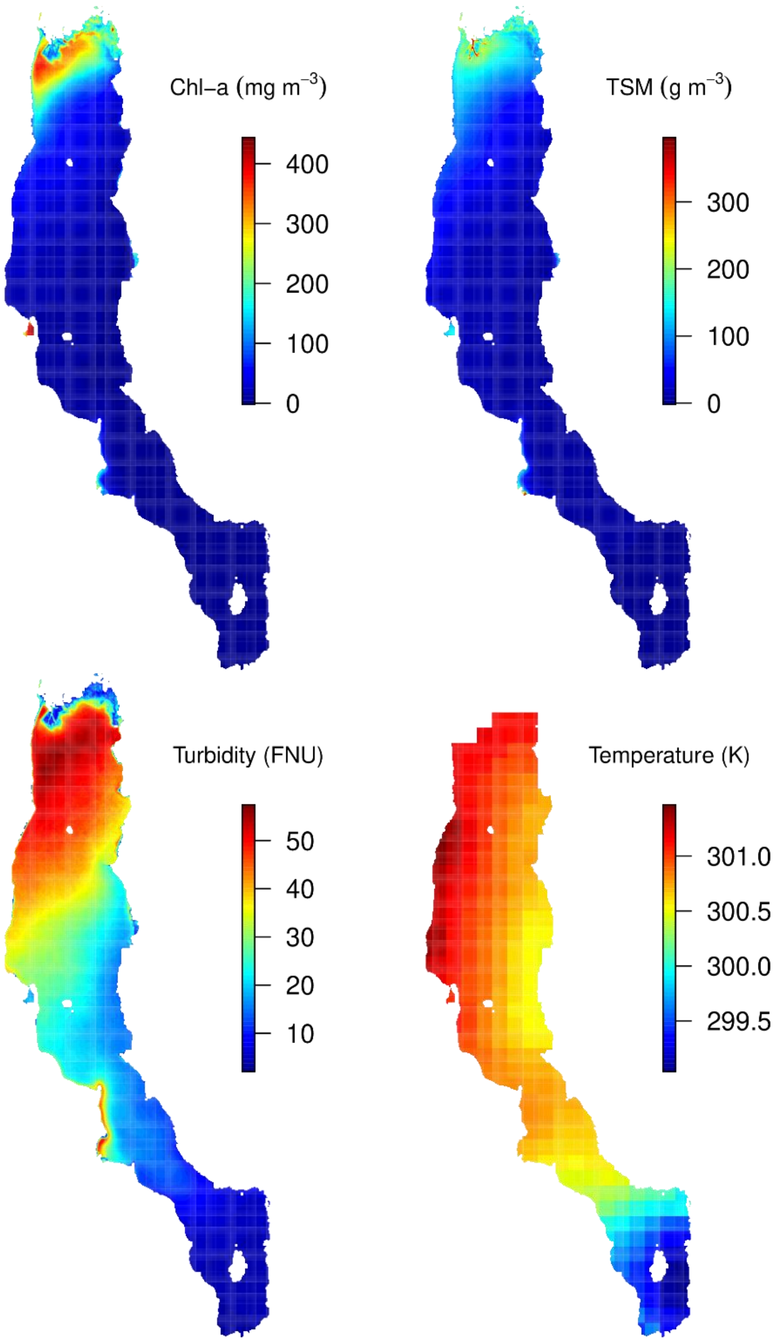

Figure 2. Long-term average maps of Chl-a, TSM, turbidity and daytime lake surface temperature, averaged over complete years (2006 – 2011) to avoid seasonal bias.

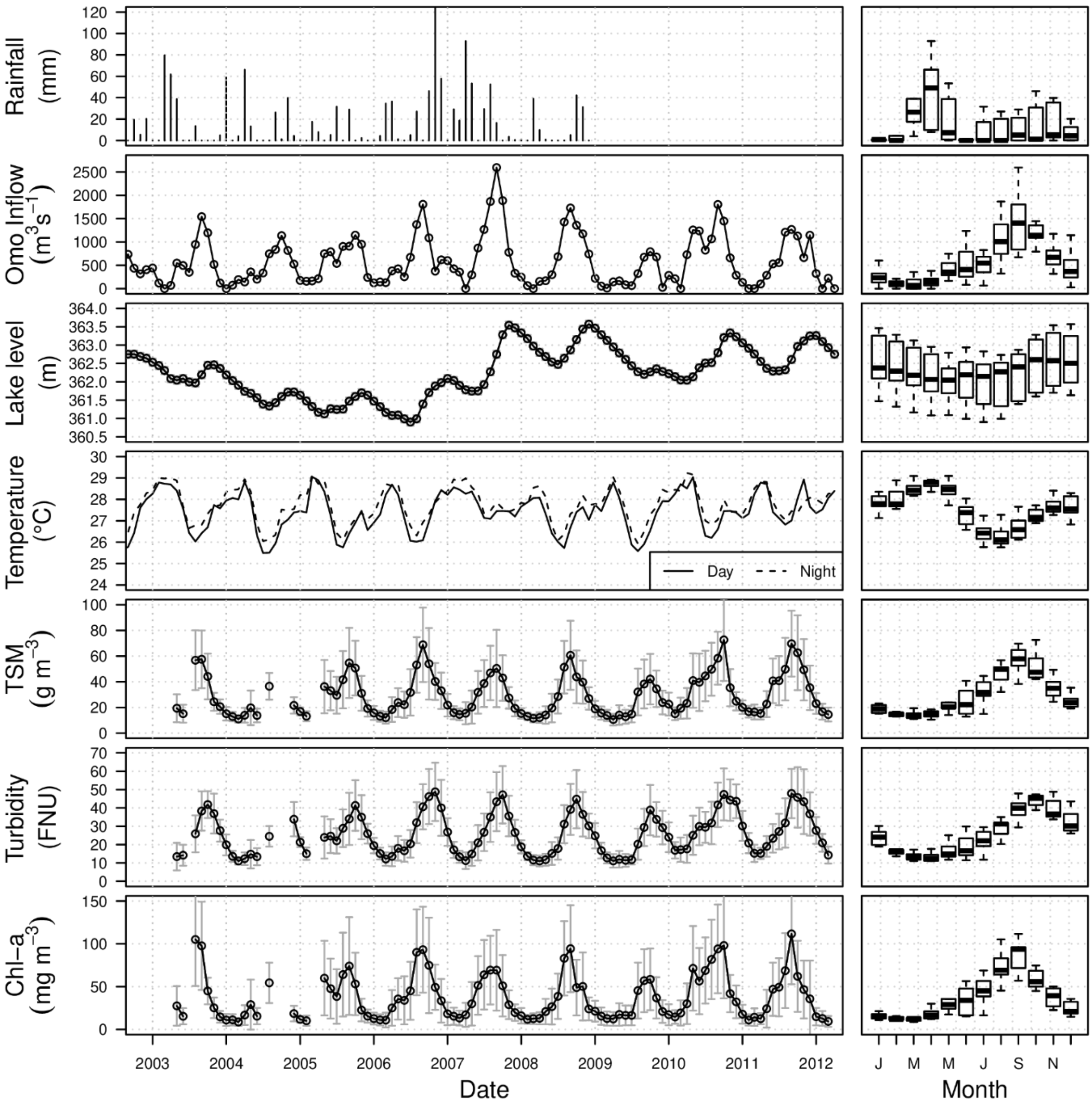

Figure 3. Time series of environmental parameters (lake levels, temperature, modelled Omo River inflows, rainfall) and lake-wide mean water quality parameters (Chl-a, TSM and turbidity) for Lake Turkana. The error bars show ± one standard deviation. Box plots included to highlight seasonal patterns.

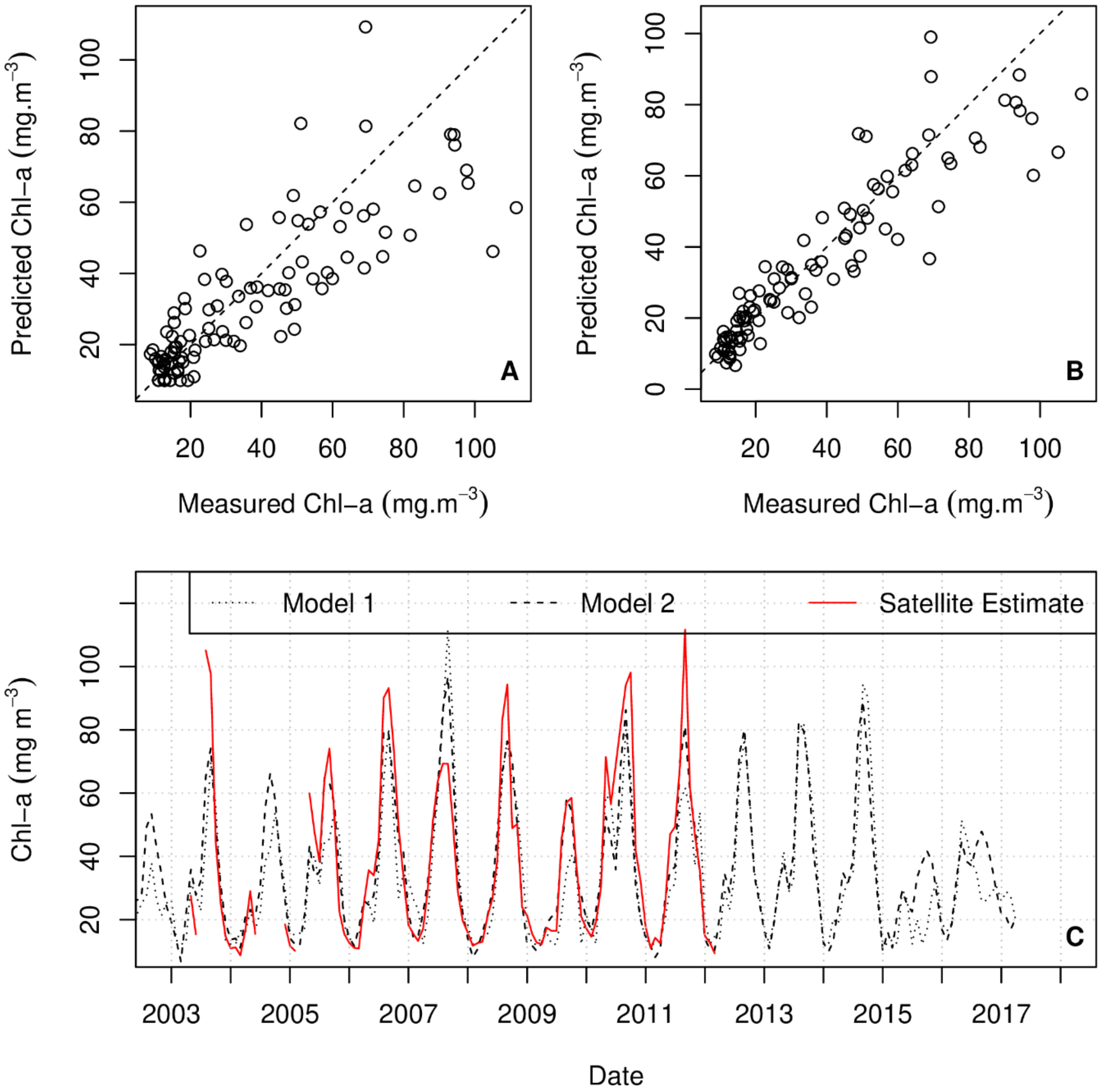

Figure 4. Satellite measured Chl-a versus predicted Chl-a estimates from Model 1 (Panel A) and Model 2 (Panel B). Time series of satellite measured Chl-a and Chl-a predicted from hydrological variables using Model 1 and Model 2 (Panel C).

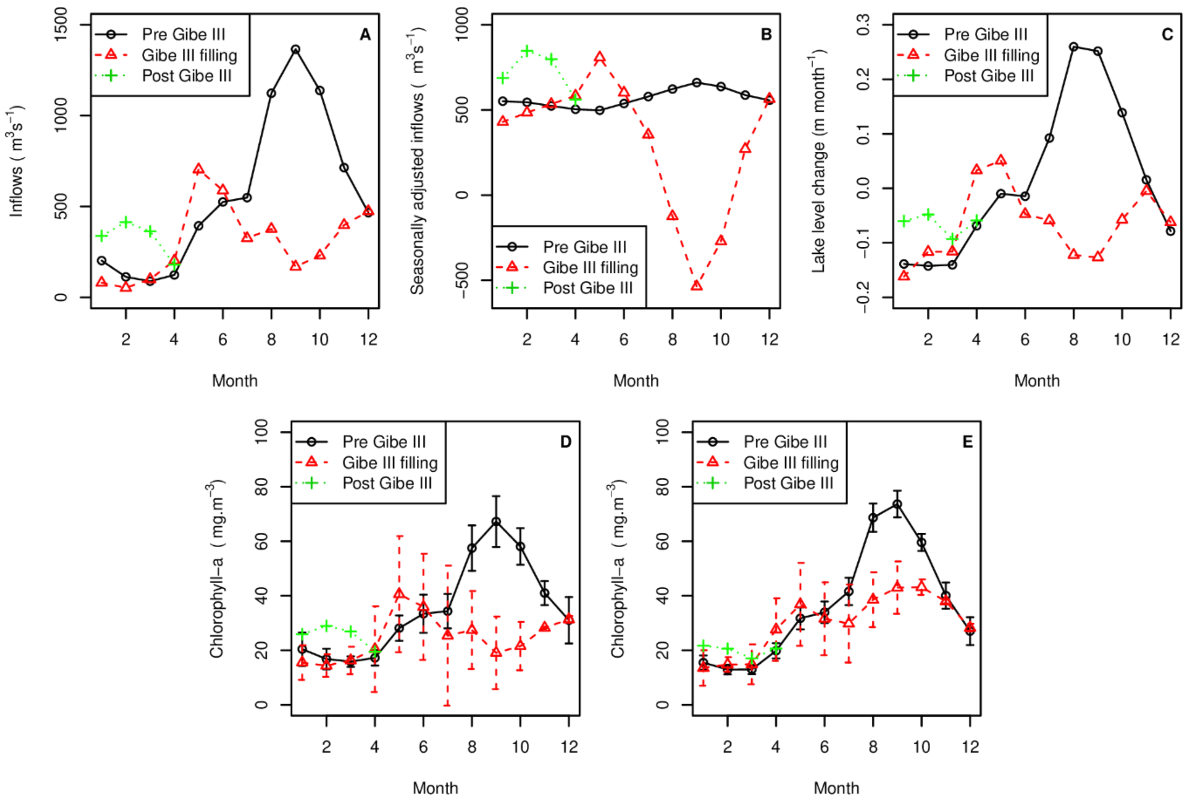

Figure 5. Monthly mean raw and seasonally-adjusted Omo inflows (Panels A and B), lake level change (Panel C) and Chlorophyll-a (Panels D and E) in Lake Turkana. Chlorophyll-a was predicted from Model 1 (Panel D) and Model 2 (Panel E). All panels show the periods pre-Gibe III (before Jan 2015); Gibe III filling (2015-2016); Post Gibe-III (2017 onwards). Error bars represent the 95% confidence internal around the mean.

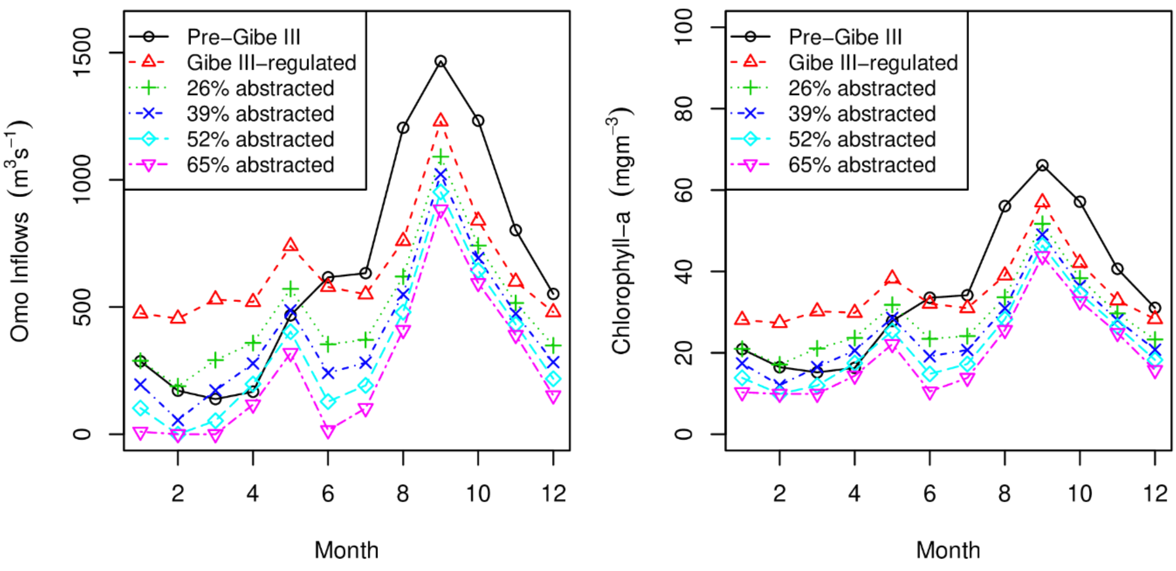

Figure 6. Monthly mean Omo inflows and lake-wide mean chlorophyll for Lake Turkana, from historic modelled inflows (for the period 1993 – 2014) and future scenarios including regulated inflows due to the Gibe III dam and different abstraction scenarios for irrigated agriculture. Chlorophyll values were calculated by applying Model 1 to the Omo inflow scenarios.